PRELIMINARY TESTS OF THE UTILITY OF HYPERSPECTRAL IMAGE DATA TO PRECISION FARMING

J. Garegnani,[a] *J. A. Gualtieri,*[a,1] *S. Chettri,*[a,1] *J. Robinson,*[a,2] *J. P. Hunt,*[a,1] *M. Bechdol,*[a,1] *A. Vermeullen,*[b,3]

Applied Information Sciences Branch, Code 935, NASA/GSFC, Greenbelt, MD 20771, U.S.[a]
Biospherics Science Branch, Code 923, NASA/GSFC, Greenbelt, MD 20771, U.S.[b]
Global Science and Technology[1]
Raytheon ITSS[2]
Science Systems and Applications, Inc[3]
jerry.garegnani@gsfc.nasa.gov (301) 286-1079 / (301) 286-1776 fax

1. INTRODUCTION

In a test of the utility of hyperspectral image data to precision farming, we have collected several inter-dependent data sets at an experimental farm on Maryland's Eastern Shore during the 1999 growing season, focusing on weed identification in corn and soybean crop fields. These data included: hyperspectral image data from an airborne instrument; ground feature location data collected with a differential GPS unit; geo-located radiometer and sun photometer measurements at ground level. In addition a database for the cost of all field inputs, materials and labor, was built to allow evaluation of the economic viability of incorporating hyperspectral data as an additional information source for precision farming.

By collecting ground based radiometer and sun photometer measurements coincident with sensor over-flights, we were able to identify and partition sources of variation in the AISA image data so that target signals could be more accurately characterized. We used this to provide atmospheric correction for our efforts to identify areas of weed infestation during the early stages of crop emergence. Later in the growing season we used these methods for identifying different strains of crops in both maturing soybean and corn fields.

2. METHODS OF DATA COLLECTION

Field experiments were conducted coordinating the AISA sensor flown aboard a twin engine Navaho aircraft by 3DI of Easton, MD with teams on the ground collecting radiometric data. The field work was conducted at Chesapeake Farms on the Delmarva Peninsula near the town of Rock Hall, MD on May 28, July 8, and August 3, 1999.

2.1. The AISA sensor

The work described here is based on data from the Airborne Imaging Spectrometer (AISA) built by Specim of Finland [1] and has a spectral range of 430 to 900 nm, a swath width of 286 pixels is imaged at a spatial resolution of 1m, 2m, and 3m for an aircraft flying at 1 km, 2 km, and 3 km respectively. In addition simultaneous down-welling irradiance is measured. The instrument orientation is monitored by an Inertial Measurement Unit, and its position is recorded by GPS (Global Positioning Satellite). The data was geo-rectified to UTM coordinates and processed to both at sensor radiance measurements, and to at sensor reflectance, by ratioing the up-welling radiance to the down-welling radiance.

2.2. Ground Truth Measurements

Three Analytical Spectral Devices hand held radiometers - two model PS2's and one model FR were used for the ground truth measurements of up-welling radiance and reflectance. Also a Microtops 2 portable sun photometer was used to gather aerosol optical thickness measurements at regular intervals during the flights. Location of sampling points and field boundaries was made with a Trimble Pro XR system. Portable stands were designed to hold the field radiometer heads and a spectralon panel (at a fixed distance from the head) for reflectance measurements. With the stands, spectral measurements at varying heights up to 2m over ground samples could be made.

3. ANALYSIS

3.1. Atmospheric Correction

An important part of applying hyperspectral data to precision farming will be monitoring temporal changes in spectral properties as an indicator of crop health. This requires that the hyperspectral imagery be transformed into reflectance spectra, which is an intrinsic property on the surface independent of solar illumination and atmospheric effects.

To perform atmospheric correction and subsequent conversion to reflectance, we have used the *three band method* of Gao et. al. [3], [4] as implemented in his ATREM_LINE code which he has made available to us. This code explicitly estimates the gaseous water content in the atmosphere on a pixel-by-pixel basis from water absorption bands and uses scene estimates for aerosol and ozone. The absorption of the atmosphere is modeled by a line-by-line model for the atmospheric gases and takes into account the scattering in the atmosphere. Thus this code can be adapted to the AISA instrument, which in our work has spectral resolution around 7 nm. Because of the limited spectral coverage of AISA, from 400 nm to 900 nm the only water absorption band that can be used is the one at 818 nm.

To assess the atmospheric correction we used 2m resolution data taken on August 3, 1999, close to solar noon, in which a "bright" road was present. No visible clouds were present at the time of the measurements. The ground radiometer measurements were taken 13 minutes after the aircraft passed over the road. Fig 1 shows a small part of a flight line with road pixels marked in red for comparison with the radiometer measurements taken at the numbered yellow points obtained by GPS.

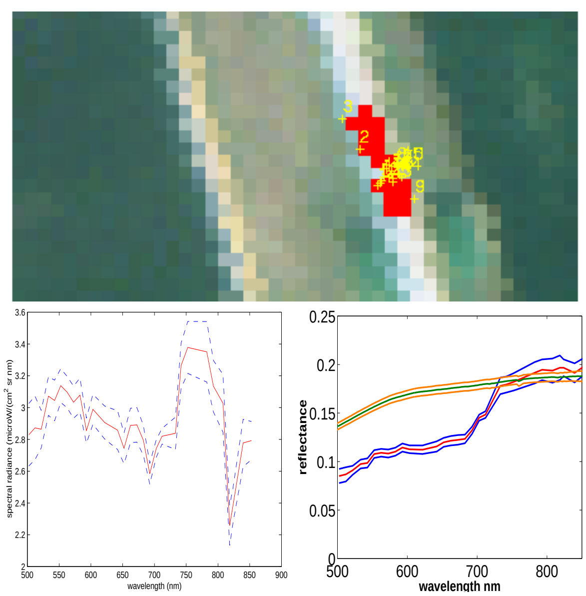

Figure 1: On the top is the AISA imagery used in the test of atmospheric correction. On the bottom left is the at sensor radiance spectra and on the bottom right is the atmospherically computed reflectance spectra in red (standard deviation in blue) and the ground measured reflectance spectra in green (standard deviation in yellow).

From the red pixels we obtain the at sensor radiance as shown in Fig. 1 (bottom left) where the vertical axis has been expanded to emphasize the spectral features. Note the water absorption band around 820 nm. Using the ATREM_LINE code with an aerosol model of 50 km visibility and ozone concentration of 0.34 atm-cm we obtain the reflectance spectra at the ground. This is shown in blue (red standard deviation) together with the ground measurements in green (yellow standard deviations) in Fig. 1(bottom right). The atmospheric correction has removed the water absorption while the lack of agreement may be due to adjacency effects.

3.2. Weed Detection

Early detection of weeds through remote sensing can be an important tool to a farmer for improving crop yield, and, if variable rate equipment for herbicide application is available, for reducing costs and reducing environmental impact. The images in Fig. 2 show the results of a minimum noise fraction (MNF) [2] classification of a corn field (right) and soybean field (left). The algorithm was applied to apparent reflectance data at 2m resolution from May 28, 1999. The colormap chosen for the corn field highlights weed infestation density; bare soil appears as blue with increasing density of weeds from green to yellow to red designed as a "spray/do not spray" tool for the farm. In the right part of Fig. 2 is

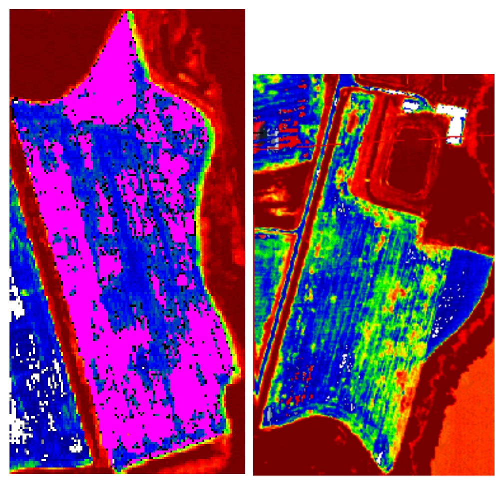

Figure 2: On the left a Vegetation index of a soybean field at early emergence. On the right a Minimum Noise Fraction classification of a corn field at early emergence.

shown a Minimum Noise Fraction [2] classification of a corn field performed on apparent reflectance spectra data. Bare soil appears as purple with increasing density of weeds from green to yellow to red.

It can bee seen that the processed hyperspectral imagery provides a useful tool for the early detection of weeds.

3.3. Differentiation of Seed Types from Mature Corn and Soybeans

The ability to differentiate seed type via remote sensing of mature crops has implications for agricultural monitoring activities. Knowledge of planted seed types in local to global

	Corn A Pioneer 34K82	Corn B Pioneer 33G26	Soy:C Asgrow AG4301	Soy:D Pioneer 9421STS
SVM	99.9	99.9	94.6	74.3
Min-Dist.	99.7	99.8	91.6	61.4

Table 1:
Performance comparison differentiating crop types.

crop monitoring activities yields important information concerning countless crop characteristics like maturation potential, health, resistance to disease/pests/drought, and potentially the quantification and assessment of Genetically Modified Organism (GMO) plantings. Recently we have applied a powerful new method of supervised classification, the Support Vector Machine (SVM), to hyperspectral data that is *not* affected by its high dimensional nature. [5], [6].

From 2m resolution data taken on Aug.3, 1999 we randomly selected 1 % of pixels in fields two kinds of corn, type A (Pioneer 34K82), and type B (Pioneer 33G26), two types of soybeans, type C (Asgrow AG4301) and type D (Pioneer 9421STS). The spectra of the training classes is shown in Fig. 3 where it is seen that differentiation is not obvious. In Table 1 is a comparison of the users performance accuracy for the SVM classifier and a minimum-Euclidean distance classifier. The SVM classifier has overall better performance, but in particular on distinguishing the soybean classes it has substantially improved performance.

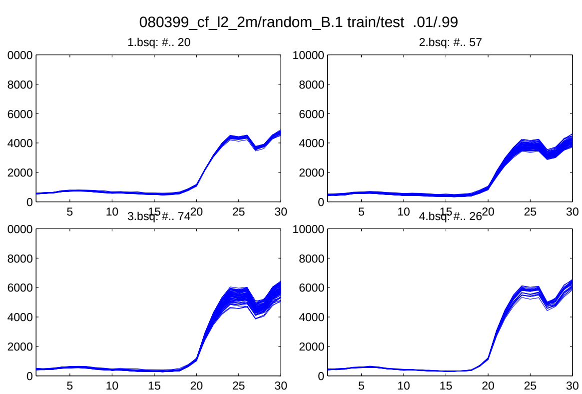

Figure 3: Training data from sensor apparent reflectance Spectra of mature crops of two different corn and two different soy bean seed types. From left to right, top to bottom we have crop type A, B, C, D.

3.4. Economic Implications

To gain insight as to how this imagery could be of economic value consider the soybean field shown in Fig. 2 The total acreage for this soybean field is 24.1 acres. The total area with indication of weed presence, (represented in pink) is 13 acres. After the flight the entire field was subsequently treated with a series of post-emergence herbicides at a total material cost of $32.40 per acre not including cost for labor and equipment.

Treating the entire field cost $780.84. Treating only the 13 acres with weeds present would cost $421.20, representing a total savings of $359.64 or $14.92 an acre. The labor and equipment cost, estimated at $5/acre, would only be saved in larger fields where entire sections were weed free. Since this condition is rare in the Delmarva Region, these savings were not included here. To take advantage of this saving, variable rate equipment for applying the herbicides must be available, as well as an estimate of the cost of producing the imagery. Neither have been included. However, we feel this does show the application of remote sensing imagery to precision farming is worthy of further study.

4. ACKNOWLEDGMENTS

For thanks concerning the SVM code see [6]. Additionally we thank Dr. Gao for providing the ATREM_LINE code used in our atmospheric correction experiments. The help of Code 923 who provided the sunphotometer and the spectrometers is gratefully acknowledged.

5. REFERENCES

[1] See the web site `http://www.specim.fi/`.

[2] J. W. Boardman and F.A. Kruse. Automated spectral analysis: a geological example using aviris data, north grapevine mountains nevada. In *Proceedings, ERIM Tenth Thematic Conference on Geologic Remote Sensing*, pages 407–418, 1994.

[3] Bo-Cai Gao and Curtis O. Davis. Develpment of a line-by-line-based atmosphere removal algorithm for airborne and spaceborne imaging spectrometers. In *Imaging Spectrometry III, Vol. 3118*, pages 132–141. SPIE, 1997.

[4] Bo-Cai Gao, K. B. Heidebrecht, and A. F. H. Goetz. Derivation of scaled surface reflectance's from aviris data. *Remote Sens. Environ.*, 44:165–178, 1993.

[5] J. A. Gualtieri and S. Chettri. Support vector machines for classification of hyperspectral data. In *This Proceedings*, 2000.

[6] J. A. Gualtieri, S. R. Chettri, R. F. Cromp and L. F. Johnson. SVM Classifiers as Applied to AVIRIS Data. *Summaries of the 8th JPL Airborne Earth Science Workshop*, pages 217–227, JPL Pub. 99-17, 1999. Available at `http://makalu.jpl.nasa.gov/docs /workshops/99_docs/toc.htm`.